Centre for Climate Change Economics and Policy

Grantham Research Institute on Climate Change and the Environment

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Simon Baptist and Cameron Hepburn

October 2012

Centre for Climate Change Economics and Policy
Working Paper No. 112

Grantham Research Institute on Climate Change and the Environment
Working Paper No. 95

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Intermediate inputs and economic productivity

BY SIMON BAPTIST AND CAMERON HEPBURN

Vivid Economics Ltd and London School of Economics, London UK

29 October 2012

Many models of economic growth exclude materials, energy and other intermediate inputs from the production function. Growing environmental pressures and resource prices suggest that this may be increasingly inappropriate. This paper explores the relationship between intermediate input intensity, productivity and national accounts using a panel data set of manufacturing subsectors in the United States over 47 years. The first contribution is to identify sectoral production functions that incorporate intermediate inputs, while allowing for heterogeneity in both technology and productivity. The second contribution is that the paper finds a negative correlation between intermediate input intensity and total factor productivity (TFP) — sectors that are less intensive in their use of intermediate inputs have higher rates of productivity. This finding is replicated at the firm level. We propose tentative hypotheses to explain this association, but testing and further disaggregation of intermediate inputs is left for further work. Further work could also explore more directly the relationship between material inputs and economic growth — given the high proportion of materials in intermediate inputs, the results in this paper are suggestve of further work on material efficiency. Depending upon the nature of the mechanism linking a reduction in intermediate input intensity to an increase in TFP, the implications could be significant. A third contribution is to suggest that an empirical bias in productivity, as measured in national ac- counts, may arise due to the exclusion of intermediate inputs. Current conventions of measuring productivity in national accounts may overstate the productivity of resource-intensive sectors relative to other sectors.

Keywords: Material intensity, material efficiency, intermediate inputs, productivity, total factor productivity, economic growth

This paper has been prepared for *Philosophical Transactions of the Royal Society A.* We are grateful to Julian Allwood, Alex Bowen, Eric Beinhocker, Nicola Brandt, John Daley, Markus Eberhardt, Simon Dietz, Ross Garnaut, Elizabeth Garnsey, Carlo Jaeger, Alan Kirman, Eric Neumayer, Carl Obst, Alan Seatter and three anonymous referees, among others, for useful discussions about the issues addressed in this paper. We are extremely grateful to Hyunjin Kim for outstandingly diligent and helpful research assistance. Hepburn is grateful to the Grantham Institute in Melbourne, Australia, for hospitality while working on the paper. Hepburn also thanks the ESRC Centre for Climate Change Economics and Policy and the Grantham Research Institute at the LSE for support. All errors remain our own.

1. Introduction

Since the industrial revolution, energy and material costs have fallen dramatically and rapid economic development has occurred along an energy- and materials-intensive growth path. Over the 20th century, despite a quadrupling of the population and a 20-fold increase in economic output, available material resources became more plentiful, relative to manufactured capital and labour, and technological advances continued to drive down their prices. Economists often omitted natural and environmental resources from production functions altogether, as capital and labour were more important determinants of output, and measurement issues meant that it was difficult to glean insights from data on material inputs.

This material-intensive economic model has substantially increased pressure on (i) environmental resources such as the climate, fisheries and biodiversity and (ii) natural resources and commodities. In a variety of domains, so-called 'planetary boundaries' appear to be being exceeded [58]. Commodity prices have increased by almost 150% in real terms over the last 10 years, after falling for much of the 20th century [28], and 44 million people fell into poverty due to rising food prices in the second half of 2010 [42].

Current environmental and resource pressures seem likely to increase as the human population swells from 7 billion to 9-10 billion and as the number of middle class consumers grows from 1 billion to 4 billion people [46].† If increases in living standards are to occur without social and environmental dislocation, major improvements in the efficiency and productivity with which we use materials and other intermediate inputs will be required.

Given these pressures, omitting intermediate inputs, particularly material inputs, from economic production functions, as is common in macroeconomic modeling, appears increasingly unwise. Production functions with capital and labour as the sole 'factors of production' may have been justified a century ago; it was a sensible modeling strategy to ignore materials, given their relative abundance and the absence of useful data. However, results in this paper indicate that it is worth exploring the possibility that omitting material inputs may lead to biased estimates of productivity.‡

This paper explores the important relationship between intermediate inputs, of which materials are a major component, and productivity. Understanding of the role of materials in the economy is currently limited by a number of elements of the standard economic approach to productivity measurement. The two most important limitations, discussed further in section 2, are:

1. The use of value-added aggregate measures. Value-added is defined as the value of total output minus the cost of raw materials, energy and other intermediate inputs. This measure is useful for analyses of economy-wide income and economic growth, because the sum of the value-added across

† Middle class consumers are defined as those with daily per capita spending of between $10 and $100 in purchasing power parity terms [46].

‡ Omitting materials also reflects an inaccurate assumption about scarcity and value. For instance, this type of assumption has led to the adoption of national accounts which do not include genuine balance sheets measuring wealth and other stocks; the is almost entirely on flows, although [3; 4; 8] provide notable exceptions. One consequence is that many nations, such as Australia, effectively account for the extraction of natural resources as a form of income, ratherthan as a partial asset sale.

all entities in the economy equates with total Gross Domestic Product (GDP). However, value-added measures have two major drawbacks in working with materials. First, they tend to require the assumption of constant and uniform use of materials over time and across sectors. Second, they exclude material use as an explanatory factor in generating national income and productivity.

2. Conceptual and practical limitations on data on 'material' inputs.
Data collected for national accounts on purchases of raw materials are not normally separated out from data on purchases of other *physical* intermediate inputs, such as components, or sometimes even from *all* intermediate inputs. This is partly due to conceptual problems of distinguishing between raw materials and processed intermediate components.

In this paper, we focus primarily on addressing the first limitation. We do so by using a 'gross output' production function, rather than a 'value added' production function. This restricts our ability to draw robust conclusions on an economy-wide scale — because many of the outputs of one firm are inputs to another firm — but it does allow us to account for heterogeneity in both intermediate input intensity and productivity across economic sectors. Generalising the analysis in this way places additional demand on the data required for empirical analysis, which means that it is not possible to simultaneously and comprehensively address the second limitation without compromising on statistical reliability. Accordingly, our empirical strategy is to first robustly establish the relationship between economic productivity and the wider notion of intermediate inputs, as used in national accounts. The application to a narrower definition of intermediate inputs is let to future work when the required data becomes available.
While we would prefer to distinguish material inputs alone, data limitations mean that in this paper an empirical analysis based solely on material inputs was not possible, and intermediate inputs are used instead. Intermediate inputs are defined as the sum of the real values of physical intermediate inputs, energy and purchased services (calculated by applying NBER deflators to the nominal monetary values of each input).†
The primary analysis of the paper uses data on industrial subsectors from the United States over the 47 years from 1958 to 2005. Material costs largely declined over this period until just after 2000, at which point they increased rapidly [34]. A secondary analysis employs firm-level data from South Korea to demonstrate that the results are not an artifact of sectorial composition. We also use the South Korean data to empirically explore the relationship between gross output and value-added measures of productivity. In both cases, we estimate or use production functions that explicitly account for the role of intermediate inputs, and then explore the association between the intermediate intensity of production, defined as the cost share of intermediate inputs in total cost, and total factor productivity (TFP). Productivity is commonly defined as a ratio of a volume (not value) measure of output (such as gross output or value-added) to a volume measure of input use [52]. In contrast, TFP accounts for impacts on total output that are not explained

† This follows the definitions used in the primary dataset we employ. While intermediate inputs are not disaggregated further in the dataset used for the main analysis, the US Annual Survey of Manufactures indicates that intermediate inputs are comprised by around 72 per cent physical inputs, 23 per cent services, and 5 per cent energy inputs.

by the (measured) inputs, including capital and labour, as discussed in section 2 below.

The analysis in this paper indicates that lower intermediate input intensity is positively associated with higher total factor of productivity, both across the U.S. sub- sectors and across the South Korean firms. In other words, firms and industries that employ modes of production that use more labour and fewer intermediate inputs appear to have overall higher total factor productivity. The results in this paper suggest that policies which encourage less intermediate input-intensive sectors or reduce the intermediate input-intensity of production may lead to increases in average productivity. Policies to promote material efficiency (or more general reductions in material intensity) should thus be explored, given the possible microeconomic and macroeconomic benefits.

The paper proceeds as follows. Section 2 sets out the theoretical economics of material efficiency, reviewing research that has employed production functions incorporating 'materials', in some form or other, and exploring the relationship with economic productivity. This section also provides the theoretical basis for the empirical part of the paper, presented in section 3. Section 3 describes the data, methodology and results of our analysis of U.S. manufacturing subsectors and South Korean firms. Section 4 explores the policy implications of our analysis and section
5 conclude.

2. The theoretical economics of material efficiency

Material efficiency is often defined as the provision of more goods and services with fewer materials [2]. As foreshadowed, the definition of materials within the engineering literature is often different to that which is employed in economics. Engineers and scientists have tended to define 'materials' to mean physical inputs such as iron ore and steel, often measured in units of mass. In contrast, economists often do not differentiate between 'materials' and other intermediate inputs aggregated together, partly because it can be difficult to distinguish 'raw' materials from other processed physical components — even materials such as cotton and timber require labour and capital to be produced. As noted above, we will use intermediate inputs as the unit of analysis in this paper, due to data constraints.

Similarly, we define the 'intermediate input intensity' of production as the *cost* share of intermediate inputs in the total *cost* of production. † While this is natural for an economist, an engineer might find it more natural to define 'intermediate input intensity' by reference to the proportion of the mass or volume of intermediate inputs in the final mass or volume of output. If firms adjust their inputs in order to maximise profits, our definition of 'intermediate input intensity' — the cost share of intermediate inputs in the total cost of production — is also equal to the percentage increase in intermediate inputs required for a one percent increase in output. This is referred to as the 'elasticity of output with respect to intermediate inputs'.

This section reviews the relevant economic literature. Subsection (a) examines the definition of intermediate inputs. Subsection (b) reviews previous efforts to incorporate intermediate inputs in economic production functions, subsection (c) sets

† Intermediate input and material intensity and efficiency are rarely examined in economics; the most closely-related research examines natural resources as a broad theoretical concept [27; 35; 64; 66].

out the theoretical links between intermediate input use and TFP, and subsection (d) establishes the basis for the empirical section of the paper.

(*a*) *The definition of intermediate inputs*

Within national accounts, materials are generally incorporated into an 'intermediate inputs' aggregate. This unhelpful state of affairs has arisen for several conceptual and practical reasons. First, as noted above, it can be difficult to conceptually distinguish raw materials from processed physical components. The examples of timber and cotton have already been noted. In addition, consider that the 'raw material' of iron ore, used in steel manufacturing, is itself the *output of* an economic sector, mining. The mining sector combines labour, capital, natural resources and yet further 'intermediate inputs' to produce iron ore. The same logic applies to a whole range of 'materials' — they themselves require a composite of capital, labour and other inputs to produce. However, there are accepted methodologies for distinguishing capital as a primary input in a way that has not yet occurred for materials, with the result the flow of the share of output accruing from material use is attributed either to labour, capital or TFP. Second, partly as a result of the conceptual difficulties, useful data on 'raw materials' for econometric analysis are not as widely available as data on the broader category of 'intermediate inputs'. Indeed, national accounts typically do not distinguish between inputs other than labour and capital; materials are combined into the intermediate inputs aggregate, which is subtracted from gross output to give value added. While an increase in the value of raw materials used would increase the value of intermediate inputs, it clearly does not necessarily follow that an increase in intermediate inputs is always due to an increase in raw material use (for example, it may be due to outsourcing of certain administrative tasks). At the sectorial level, some national accounts (such as the US and the EU) distinguish between energy and other intermediate inputs, while in other cases services are further separated from other intermediate inputs. As will be explained in section 3, the data required in order to allow heterogeneity in input use and in productivity constrain us to adopt these wider definitions†.

(*b*) *Intermediate inputs in economic production functions*

Materials have occasionally been included in the production functions of theoretical economic growth models exploring the sustainability of economic growth. For instance, theory indicates that sustainable growth may be possible, provided that human-made capital and other replacement resources substitute for depleted natural resources [64]. Technological advances and capital accumulation might also offset declining natural resources, provided the rate of technological advance is high

† One possible route to construct a more disaggregated view would be to use input-output tables, such as those of the OECD, and assume that all inputs from certain sectors (e.g. mining into manufacturing) are raw materials. However, many more sectors are aggregated together in that dataset, so this would imply a substantial reduction in the number of observations available. One route to overcome this would be to assume that sectors have identical production functions in different countries and thereby increase the number of available observations. But this solution obviously comes with its own drawbacks.

enough [66]. ‡ Empirically, however, it appears that current investments in human and manufactured capital by several countries are insufficient to offset the depletion of natural capital [3].

The increases in energy prices in the 1970s stimulated much research into energy consumption and its relationship with gross output [16; 60], including work on input-output formulations [39]. This led to an interest in directly accounting for ‘intermediate inputs’ such as materials, energy, and services, in the production function. Since then, many studies have estimated KLEM (capital, labor, energy, and materials) and KLEMS (capital, labor, energy, materials, and services) production functions, for data as early as 1947 [14].† These various research efforts provide a useful starting point for this paper, but do not provide any investigation of the relationship between material inputs and productivity.

More generally, research in this broad area has focused instead on the relationship between productivity and energy consumption [5; 60–62] or energy prices [16; 18; 38], rather than material use. For instance, empirical studies of the US economy have shown long-term trends in the relationship between energy use and productive efficiency [60; 61] and Jorgenson [44] found that declining energy intensity is correlated with higher productivity in manufacturing industries in the US, although this may not have been caused by improvements in energy efficiency. But no research has considered whether such results for energy use are observed for material use.

(*c*) *Total factor productivity*

Productivity has different definitions in different contexts. In national accounts, it is typically measured as the ratio of outputs, measured by mass or volume (not value), to inputs, measured by mass or volume [52]. In the economic growth literature, there are various productivity measures, including ‘labour productivity’ — value-added per worker — and as ‘total factor productivity’ (TFP), which is the constant term in the production function (loosely, that part of output which cannot be explained after accounting for the application of defined inputs including capital and labour).

TFP is not directly measured, but emerges as the residual in the regression of total output on measured inputs. So, for instance, if important inputs are omitted, measured TFP may be biased upwards. Measures of TFP from the early economic growth literature [63; 67] were subsequently used as the basis for analysis of productivity growth across firms, industries, and countries [21; 48–50]. Early studies tended to estimate TFP by representing the production process using a value-added function [12], in which ‘value added’, V, is related to gross output, Y, and inter- mediate inputs, M, as:

‡ The specific requirement is that the rate of technical change divided by the discount rate is greater than the output elasticity of resources [66].

† It is long been argued that energy is an additional and significant input in the production function and that it cannot simply be substituted for by other inputs [22; 25; 26; 35; 65]. Ayres argues that ‘energy services’ — energy inputs multiplied by an overall conversion efficiency — are a key driver of economic growth, and that incorporating energy as a factor of production increases the explanatory power of traditional production functions [5–7]. This literature is relevant here, because it demonstrates the impact of omitting relevant inputs from the production function.

$V = Y - M$

(2.1) a value-added estimation approach is commonly employed to determine productivity. This is partly because it is consistent with aggregation up to the economy- wide scale, but also because of a lack of data available to base the analysis on gross output. However, as noted above, the value-added approach has several limitations [52]. By definition, because it adjusts for all intermediate inputs, such as materials, it does not take into account the contribution of inputs other than capital and labour. The value-added approach therefore implicitly assumes that technical change only operates on capital and labor inputs, and that all other inputs are used in fixed proportions. Generally, the hypothesis that technology affects only primary inputs has not held up to empirical verification, and technical change has been observed to be a complex process, with some changes affecting all factors of production simultaneously, while other types of change affect individual factors of production separately [31]. Furthermore, the value-added approach does not correspond directly to a specific model of production [19]. When data allow, the gross-output approach will be preferred [11] for some purposes, such as those in this paper, while the value-added approach will be preferred for others.

The relationship between TFP and 'technology choice' — the choice of the mix of labour, capital and intermediate inputs, represented formally by the coefficients of the production function — has not, to our knowledge, been explored in the literature. Yet determining whether there is a relationship between the input intensity of different production techniques and total productivity is important, because it would help firms and policymakers to increase productivity. This paper attempts to conduct such an analysis using empirical methods, examining the relationship between TFP and the intermediate input intensity of production, as measured by the output elasticity of intermediate inputs. The next section explains our methodological strategy.

(*d*) *Theoretical basis for the empirical analysis*

We define the gross-output and the value-added production functions and explicitly set out the measure of productivity adopted. Let Y represent real gross output, K be the value of the real capital stock, L a measure of real labour input, and M the real value of intermediate inputs. Let t and i be indices representing time and individual entities (such as firms, sectors or countries) respectively. Recognising various caveats about aggregate production functions [32; 43; 47; 59], if we take the Cobb-Douglas functional form [23] as a first-order logarithmic Taylor series approximation of the production function, the value-added specification is given by:

$$\ln V_{it} = \ln a_{it} + b_{K_i} \ln K_{it} + b_{L_i} \ln L_{it}, \quad (2.2)$$

$$V_{it} = Y_{it} - M_{it}. \quad (2.3)$$

The gross output specification is given by:

$$\ln Y_{it} = \alpha_{it} + \beta_{K_i} \ln K_{it} + \beta_{L_i} \ln L_{it} + \beta_{M_i} \ln M_{it}. \quad (2.4)$$

The production function is said to have constant returns to scale if $\beta_K + \beta_L + \beta_M = 1$; this is equivalent to the function being linearly homogenous. If

this condition holds, there is a proportionate relationship between inputs and output; for example, if an industry has 10 per cent more of each input it will produce10 per cent more output. If the sum of the coefficients is less than (greater than) unity, the industry is said to have decreasing (increasing) returns to scale and the industry would consequently be more profitable by becoming smaller (larger). Constant returns to scale are sometimes imposed when sectorial or economy-wide production functions are estimated for two reasons: firstly, economic theory suggests that this condition should hold where markets are competitive and, secondly, the estimated output elasticity of capital is often insignificant or even negative in the absence of the constant returns assumption due to measurement difficulties. The null hypothesis of constant returns to scale is rejected in some, but not all, of the sectors we consider. Results are presented both with and without this restriction, and the findings of the paper hold in either case. The estimates β in the logarithmic specification of equation 2.4 are equivalent
to the output elasticity of each input; for example, the coefficient β_M can be interpreted as saying that a one per cent increase in the amount of intermediate inputs will increase output by β_M per cent. Note that there is a distinction is between the intermediate input intensity of production, as defined by the coefficients of the production function, and the physical volume of intermediate inputs which a firm or sector uses. The production function determines the output which would be expected to be generated from a certain set of inputs; but the exact choice of input factor ratios will be determined by the reactions of a profit-maximising firm subject to the fixed constraints of factor prices and the production function. The ratio of intermediate inputs to other factors of production (e.g. intermediate inputs per worker) will vary with factor prices even if the production function is fixed (i.e. lower intermediate input prices will mean more intermediate input use but not a different intermediate input intensity using our measure).

The value-added production function is valid if all intermediate inputs, including materials, are separable from other inputs; there is perfect competition, no changes in the rate of outsourcing and homogeneous technology. Biases from value-added production functions can arise if any of these conditions is not met, which is why employing the gross-output production function to derive econometric estimates of total factor productivity is preferred for our analysis. Furthermore, we show that there is a systematic divergence between measures of total factor productivity based upon the gross output and value-added production functions, and that the size of this divergence is a function of the intermediate input intensity of production. Value added is an important concept not only because it is the dominant specification for accounting for cross- and within-country income differences, but also because it forms the analytical underpinning for national accounting of GDP. Value-added measures also capture the extent to which an industry generates national income (rather than output). It is therefore of great interest to understand the nature and extent of any impact on productivity measurements from the exclusion of intermediate inputs.

Consider the relationship between the gross output and value-added measures of TFP: what if the gross output model is given by equation 2.4 but we estimate equation 2.2? The first order conditions for profit maximisation can be derived by taking the marginal product of each factor, i.e. the derivatives of the 3-factor gross output production function in equation 2.4, and setting these equal to factor prices and solving the three resulting simultaneous equations for the input quantities of

K, L *and* M. Letting p_F represent the price of factor F *and* letting $A = e^{\alpha}$ we have:

$$M = \frac{Y}{A}\left[\left(\frac{p_K}{\beta_K}\right)^{\beta_K}\left(\frac{p_L}{\beta_L}\right)^{\beta_L}\left(\frac{p_M}{\beta_M}\right)^{\beta_K+\beta_L}\right]^{1/(\beta_K+\beta_L+\beta_M)}. \quad (2.5)$$

Without loss of generality, we assume constant returns to scale for simplicity and write equation 2.5 as $M = \gamma \frac{Y}{A}$ (note that prices and the output elasticities are taken to be fixed so γ is a constant). In order to understand the bias in the coefficients in equation 2.2 we want to express the true model of production (firms physically produce gross output, e.g. tonnes of steel, rather than value-added which is rather an accounting construct derived from gross output) in a form that corresponds to the value-added model and then compare coefficients. Repeated substitution of equation 2.4 into equation 2.2, using equations 2.3 and 2.5, and suppressing subscripts for notational clarity, gives:

$$\begin{aligned}
\ln V &= \ln Y + \ln\left(1 - \frac{M}{Y}\right) \quad (2.6)\\
&= \ln A + \beta_K \ln K + \beta_L \ln L + \beta_M \ln M + \ln\left(1 - \frac{\gamma}{A}\right)\\
&= \ln A + \beta_K \ln K + \beta_L \ln L + \beta_M [\ln Y - \ln A + \ln \gamma] + \ln\left(1 - \frac{\gamma}{A}\right)\\
&= \ln A + \frac{\beta_M}{1-\beta_M} \ln \gamma + \ln\left(1 - \frac{\gamma}{A}\right) + \frac{\beta_K}{1-\beta_M} \ln K + \frac{\beta_L}{1-\beta_M} \ln L.
\end{aligned}$$

In our 3-factor model with constant returns to scale, the relationship between the value-added and gross output coefficients is therefore:

$$\ln a = \ln A + \frac{\beta_M}{1-\beta_M} \ln \gamma + \ln\left(1 - \frac{\gamma}{A}\right), \; b_K = \frac{\beta_K}{\beta_K + \beta_L}, \; b_L = \frac{\beta_L}{\beta_K + \beta_L}. \quad (2.7)$$

Equation 2.7 shows that estimates of TFP from a value-added production function will be biased estimates of gross output total factor productivity and the size of this bias will be increasing in β_M. Value-added is a useful summary statistic for discussing the distribution of income and in deriving measures of productivity that reflect the extent to which economy-wide income cannot be explained by the accumulation of capital and labour. However, the omission of intermediate inputs and the resultant divergence in measures of TFP means that the underlying productivity of the production process is better measured using the gross-output production function.

In the empirical work which follows in section 3, we investigate the observed pattern between underlying productivity and intermediate input intensity using the gross-output specification.

3. Empirical analysis

In this section, we use sectorial and firm-level data to investigate the hypothesis that a higher intermediate input intensity is associated with lower underlying TFP. We also use firm-level data to show that estimates of value-added total factor productivity are indeed divergent in the manner derived in equation 2.7.

It is worth emphasizing the stringent data requirements in order to relax the conventional assumptions that intermediate inputs enter the production function in an identical way for all sectors and that productivity is unrelated to intermediate input use. In order to obtain a single data point with these generalizations, it is necessary to estimate a production function. The estimated production function coefficients and the estimate of TFP then provide a single observation, which can be used to investigate the question of the nature of the relationship between intermediate input intensity and total factor productivity. Therefore it is necessary to collect enough data to estimate each relevant production function, and then to repeat the process a sufficient number of times in order to have enough data points for the ultimate analysis. Note also that each of the observations in the ultimate analysis must be sufficiently related such that it is sensible to compare them.
The dataset we have employed satisfies these stringent data requirements. In order to obtain enough observations to allow for heterogeneity to investigate the relationship between input use and total factor productivity at the sectorial level, we have had to accept a level of aggregation of inputs which is higher than we would prefer (i.e. intermediate inputs rather than materials).

(*a*) *Data*

We investigate our hypothesis primarily using the NBER-CES manufacturing industry database, and full details of variable definitions and database construction are available from the website of the NBER [13]. The dataset is a panel of 473 manufacturing industries defined to the six-digit level (based upon NAICS codes) from 1958 to 2005. The data are unbalanced in that some industries enter or leave manufacturing due to a change in the industry coding structure in 1996, but all data have been coded so that they are consistent with the current sectorial definitions.
The dataset contains annual industry level data on employment and hours, nominal value of shipments, value-added, capital stock and intermediate inputs, along with price indices for sales, capital stock, and intermediate inputs. Firm gross out- put is constructed as the value of shipments plus the change in inventories, using the price index for shipments to deflate into real values. Hours worked are calculated by multiplying total employment by the average hours worked by production workers: the hours of non-production workers are not available and so we assume that non-production workers in a sector put in the same number of hours as production workers. Real value-added is calculated by using the price indices for shipments and materials, with the price index for shipments being used as a deflator for inventories. Two NAICS industries — 334111 (computers) and 334413 (semiconductors), are excluded from the analysis due to difficulties in constructing accurate price deflators. We do not have data on human capital, such as average education of workers, at the subsectoral level but, in the context of models with heterogenous technology, human capital can be controlled for by the inclusion of intercept and time trend terms under plausible conditions [30].

(*b*) *Specification of intermediate input intensity and parameter heterogeneity*

In this analysis, 'technology' is used to refer to the set of coefficients β_K, β_L, β_M, while TFP is defined as the constant term α, and is allowed to vary over time and

NAICS code	Sector description
311	Food Manufacturing
312	Beverage and Tobacco Product Manufacturing
313	Textile Mills
314	Textile Product Mills
315	Apparel Manufacturing
316	Leather and Allied Product Manufacturing
321	Wood Products
322	Paper Products
323	Printing and Related Support Activities
324	Petroleum and Coal Products
325	Chemical Products
326	Plastics and Rubber Products
327	Non-metallic Mineral Products
331	Primary Metal Products
332	Fabricated Metal Products
333	Machinery
335	Electrical Equipment, Appliances and Components
336	Transportation Equipment
337	Furniture and Related Products
339	Miscellaneous Manufacturing

Table 1. *NAICS industry definitions.*

across sectors through the inclusion of binary dummy variables. The least restrictive assumption we could make on technology in this context would be to allow each six-digit industry to have its own set of production function coefficients, possibly varying over time. However, this would have the disadvantage of reducing the sample size available for each estimated production function, would not allow for the exploitation of the panel dimension of the dataset and, most importantly, would not allow unrestricted TFP evolution as there would be insufficient observations to include year dummies. We therefore allow for technological heterogeneity at the three-digit level (i.e. the industries defined in table 1), and assume that every six-digit subsector of a three-digit industry has common technology. Technology is also held to be fixed within a three-digit industry over time.† This is, of course, more restrictive than allowing technology to differ by six-digit subsector, but less restrictive than estimating a production function at the level of aggregate manufacturing or of the aggregate economy. It has recently been argued that the focus in the literature on cross-country and cross-sectorial production functions on matters of endogeneity and specification has neglected the important possible role of parameter heterogeneity [30]. This paper presents evidence that one critical element of this heterogeneity is in the role of intermediate inputs in production.

If prices of inputs and technology are taken to be exogenous and there is perfect competition and constant returns to scale, then the first-order conditions of profit maximisation in equation 2.4 imply that the share of intermediate inputs in total cost will be equal to β_M. An augmented condition holds if these restrictions do

† This, along with the inclusion of time dummies, means that secular trends in productivity and the share of intermediate inputs are not the cause of our results; rather, they are driven by the cross-section variation between sectors.

not apply. While only the exogeneity restrictions are imposed in our modeling, we use this result as a motivation for our empirical definition of intermediate input intensity: a sector is said to be more intensive if the coefficient β_M is higher, and this paper aims to investigate the relationship between total factor productivity and intermediate input intensity by estimating production functions for different subsectors of US manufacturing.†

(*c*) *Estimation strategy*

We employ econometric methods to estimate the parameters of an aggregate production function and express productivity in terms of the estimated parameters. Our approach is different to the standard 'growth accounting' approach [31; 45]. The growth accounting approach is to use a non-parametric technique that weights different types or qualities of factors by income shares [40; 51]. While the growth accounting approach has often been preferred due to its less stringent data requirements, it requires five key assumptions in order to be valid. First, it assumes a stable relationship between inputs and outputs at various levels of the economy, with marginal products that are measurable by observed factor prices [10]. Second, the production function used must exhibit constant returns to scale [51]. Third, the approach assumes that producers behave efficiently, minimizing costs and maximizing profits [51]. Fourth, the approach requires perfectly competitive markets within which participants are price takers who can only adjust quantities [51]. Fifth, a particular form of technical change must be assumed.

In contrast, the econometric methods we employ do not require the *a priori* assumptions of the growth accounting method. Rather, they enable these assumptions to be tested [15]. Equations 2.2 and 2.4 are estimated using a range of econometric techniques.† Identification problems [47] can be overcome using the plausible and widely-made assumption that the prices for inputs and outputs vary across subsectors.‡

† Equation 2.4 shows why material or intermediate input per unit of output is not an appropriate measure to investigate our hypotheses, as an increase in TFP (i.e. α) will trivially decrease material per unit of output.

† The literature on estimating production functions, particularly in the context of panel data with a long time series dimension is rapidly evolving. One of the key difficulties in this literature has been finding a specification and an estimation method which achieve both economic and econometric regularity [31]. A recent survey of the state of production function estimation is given by [30], which contains a full discussion of the different estimation techniques available and the conditions required for each of them to produce unbiased and efficient estimates of the true underlying parameters.

‡ If all inputs are costlessly adjustable and chosen optimally then, if prices are common, a Cobb-Douglas production function will be unidentified [17]. Taking the first derivative of a Cobb-Douglas production function leads to a first-order condition where quantities are functions of prices and the (sector or firm-specific) TFP term. So, with common prices, inputs are all collinear with the TFP term and so are unidentified. This problem is mitigated in the presence of adjustment costs or where sectors face different factor prices. Note that input prices faced by sectors can still differ even if one were to believe that input markets are perfect. For example: the effective price of labour will differ with commuting distances; the price of capital will differ with proximity and expertise of repair and maintenance firms, which themselves may be sector-specific, or with credit constraints. Contracts for the supply of raw materials will contain prices which will vary depending on when the contract was signed and the relative use of spot or forward markets. Transport costs for physical intermediate inputs will also be firm and sector specific. And so on. Even if prices

We employ four different econometric techniques: ordinary least squares (OLS), the standard panel data fixed effects estimator (FE), the mean groups estimator (MG) [56] and the common correlated effects mean group estimator (CCEMG) [55]. These latter two estimators allow for more general forms of cross-section and time series dependence, as well as forms of heterogeneity in the error structure. The OLS estimator will be valid if statistical error for each observation is independently and normally distributed. A fixed effects estimator relaxes this assumption by allowing for common time-invariant factors within a subsector. The mean group's estimator will yield consistent estimates so long as there is not heterogeneity in unobserved variables and errors are stationary. The CCEMG estimator allows for heterogeneity in the unobservables and allows for cross-section dependence resulting from unobserved factors common between sectors (e.g. Common shocks affecting more than one subsector). These issues would require a fuller treatment in order to precisely identify the production function parameters and to make possible statements about a causal impact of intermediate input intensity on total factor productivity, and so we do not make claims of causality in this paper. Rather, we seek to demonstrate that intermediate input intensity is related to total factor productivity and that the relationship is robust to a number of different econometric approaches.

The key results of this paper — that sectors with higher intermediate input intensity tend to have lower levels of TFP and that value-added estimates of TFP have a bias which is increasing in intermediate input intensity — are robust to these choices of estimation technique. We present the results from all four estimation methods graphically, in each case with and without imposing the assumption of constant returns to scale. For the sake of brevity, only the OLS results are presented in table form in the main body of the paper, but the results from the other estimators in table form are available from the authors upon request.

(*d*) *Results and Discussion*

The results from the OLS regression for each of the twenty industries considered are presented in table 2. The production function coefficients are generally plausible: the coefficients on labour and intermediate inputs are all positive, as are the majority of those on capital. Due to difficulties in the valuation of capital stock it is not uncommon for some estimates of β_K to be negative or poorly identified, and constant returns to scale are often imposed to achieve regularity given that the condition should be satisfied in an industry in equilibrium.† For example, Burnside [20] concludes that constant returns to scale is probably an appropriate restriction for US sectorial-level production functions. Both the restricted and unrestricted results are presented here, and the conclusions follow regardless.

While our primary interest is in the pattern between the sets of coefficients α, β_K, β_L and β_M, we first describe their absolute estimates to give a feel for the results. The highest intermediate input intensity (as measured by β_M) is observed in the apparel (315) and leather (316) sectors, where intermediate inputs account for around 90 per cent of total inputs; the lowest is found in electrical equipment (335)

were to be identical between sectors, the identification problem can be solved provided adjustment costs between inputs differ by firm or sector, as would be expected.

† Recall that because α is defined as the constant term in a logarithmic equation, negative values simply refer to levels of TFP of between zero and one and are not cause for concern.

and furniture (337) manufacturing, where the share is under 50 per cent. Total factor productivity is highest in fabricated metal products (332) and machinery (333) and lowest in leather products (316) and plastics and rubber (326).

The relationship between the intermediate intensity of an industry and its total factor productivity is shown in figure 1. There is a clear relationship in the pat- tern of coefficients across industries: those sectors with a higher intermediate input intensity tend to have lower total factor productivity. This pattern is repeated for the fixed effects estimator, shown in figure 2, and the MG and CCEMG estimators, shown in figure 3.

The β coefficients of the production function sum to a quantity close to unity for all industries where the estimation is unrestricted. Therefore, a negative pattern between β_M and TFP implies that there is likely a positive pattern between TFP and at least one of the other coefficients. Figure 4 depicts the observed pattern between the labour output elasticity and TFP using the results from table 2. There is a strong positive relationship: sectors which are more intensive in their use of labour inputs tend to have higher TFP. There is no clear pattern in relation to capital intensity, not shown for brevity. The fact that labour-intensive sectors have higher TFP and intermediate input-intensive sectors have lower TFP is reminiscent of the (controversial) 'double dividend' hypothesis that replacing labour taxes with environmental taxes might reduce the costs imposed by the tax system [36].

Because TFP is, by its very nature, capturing unobserved elements of the production process, it is not possible to infer from this analysis the precise nature of the relationship between the two. It may be the case that reducing intermediate input intensity causes changes in unobserved factors which lead to increase TFP directly, or it may be that changes in an associated unobservable factor result both in a lower share of intermediate inputs and higher TFP. In the former case, policies to reduce intermediate input intensity would have a direct TFP benefit; in the latter case, it would depend upon whether the policy acted via the relevant unobservable factor.†

Our analysis does not attempt to discriminate between possible causes of the observed correlation between TFP and β_M. Future research, with a richer data set, could explore the following hypotheses. First, as suggested by equation 2.7, it may be that rents from natural resources in the value-added/GDP framework are being ascribed to TFP. Second, both the constant and slope parameters of the production function could be jointly determined fundamental parameters of the production function. Third, the pattern of outsourcing and vertical integration both between sectors and within a sector over time might differ in such a way that is systematically related to TFP. This list of possible drivers of the correlation is not exhaustive.

We conduct a further piece of analysis to address a possible concern that the sectorial relationship is an artifact of the aggregation of firms, and that any variation can be solely accounted for by sectorial composition alone rather than by

† This could be explored by allowing the production function parameters to vary over time, but we do not have sufficient data to robustly estimate production functions for a single industry over time without imposing restrictions on the nature of technology evolution. The data requirements to do this would be strenuous indeed; a large data set is required even just to generate an estimate of a production function, which provides only a single observation for the analysis of the TFP-technology nexus.

NAICS code	α (TFP)	β_K	β_L	β_M	α (CRS)	β_K (CRS)	β_M (CRS)
311		0.22*	0.23*	0.53*		0.14*	0.62*
		0.01	0.01	0.01		0.01	0.01
312	0.28*	-0.05*	0.13*	0.83*	0.00	0.09*	0.71*
	(0.09)	(-0.02)	(0.02)	(0.02)	(0.06)	(0.02)	(0.01)
313	-0.51*	0.18*	0.16*	0.62*	-0.34*	0.18*	0.58*
	(-0.09)	(0.03)	(0.02)	(0.03)	(-0.06)	(0.03)	(0.03)
314	-0.19	-0.07*	0.17*	0.81*	0.15*	0.01	0.61*
	(-0.10)	(-0.03)	(0.03)	(0.04)	(0.07)	(0.03)	(0.04)
315	-0.58*	-0.01	0.05*	0.90*	-0.47*	-0.01	0.83*
	(-0.07)	(-0.01)	(0.01)	(0.01)	(-0.04)	(-0.01)	(0.01)
316	-1.19*	0.06*	0.08*	0.91*	-0.63*	0.01	0.88*
	(-0.12)	(0.03)	(0.03)	(0.04)	(-0.07)	(0.02)	(0.03)
321	-0.56*	-0.05*	0.29*	0.79*	-0.39*	-0.05*	0.83*
	(-0.09)	(-0.02)	(0.02)	(0.02)	(-0.07)	(-0.02)	(0.02)
322	-0.16*	0.12*	0.17*	0.66*	-0.10	0.07*	0.68*
	(-0.08)	(0.01)	(0.02)	(0.02)	(-0.06)	(0.01)	(0.02)
323[a]	0.28*	0.05*	0.37*	0.57*	0.51*	0.00	0.58*
	(0.06)	(0.02)	(0.02)	(0.02)	(0.06)	(0.02)	(0.02)
324[a]	-0.53*	0.08	0.15*	0.76*	-0.34*	0.01	0.81*
	(-0.09)	(0.05)	(0.05)	(0.06)	(-0.08)	(0.03)	(0.03)
325	-0.30*	0.03*	0.47*	0.64*	0.05	0.05*	0.70*
	(-0.06)	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)
326[a]	-0.67*	0.02	0.16*	0.82*	-0.41*	0.07*	0.74*
	(-0.08)	(0.02)	(0.02)	(0.03)	(-0.07)	(0.02)	(0.03)
327[a]	-0.08	0.16*	0.27*	0.56*	-0.06	0.11*	0.64*
	(-0.07)	(0.02)	(0.02)	(0.02)	(-0.05)	(0.01)	(0.02)
331	0.09	0.01	0.31*	0.66*	0.15*	0.07*	0.62*
	(0.06)	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)
332	0.59*	0.07*	0.39*	0.50*	0.60*	0.08*	0.47*
	(0.06)	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)
333	0.32*	0.05*	0.43*	0.54*	0.58*	0.02	0.56*
	(0.06)	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)
335	0.17*	0.29*	0.44*	0.31*	0.43*	0.27*	0.35*
	(0.09)	(0.02)	(0.01)	(0.02)	(0.05)	(0.02)	(0.02)
336	-0.35*	0.00	0.42*	0.67*	0.09*	0.10*	0.62*
	(-0.05)	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)
337	0.13	0.21*	0.30*	0.47*	0.09	0.05*	0.62*
	(0.10)	(0.02)	(0.02)	(0.04)	(0.08)	(0.02)	(0.04)
339	-0.56*	0.14*	0.28*	0.65*	0.18*	0.11*	0.58*
	(-0.07)	(0.01)	(0.02)	(0.02)	(0.05)	(0.01)	(0.02)

Table 2. *The dependent variable is log of real output in 1987 $US. Observations have been weighted according to employment in the sector. Constant returns to scale in K, L and M have been imposed in columns denoted (CRS), although the null hypothesis of CRS was rejected in all industries other than those denoted with an a. Note that in the CRS estimates* $\beta_K + \beta_L + \beta_M = 1$ *and hence* β_L *is not reported. Year dummies were included but have not been reported. Standard errors in parenthesis and * indicates significance at* $p < 0.05$. *Industry 311 is the omitted category and so* α *in that industry is implicitly defined as zero. The null hypothesis of common technology across these industries is easily rejected. The* R^2 *of this regression is 0.9996 and the residual standard error is 1.05 on 20339 degrees of freedom.*

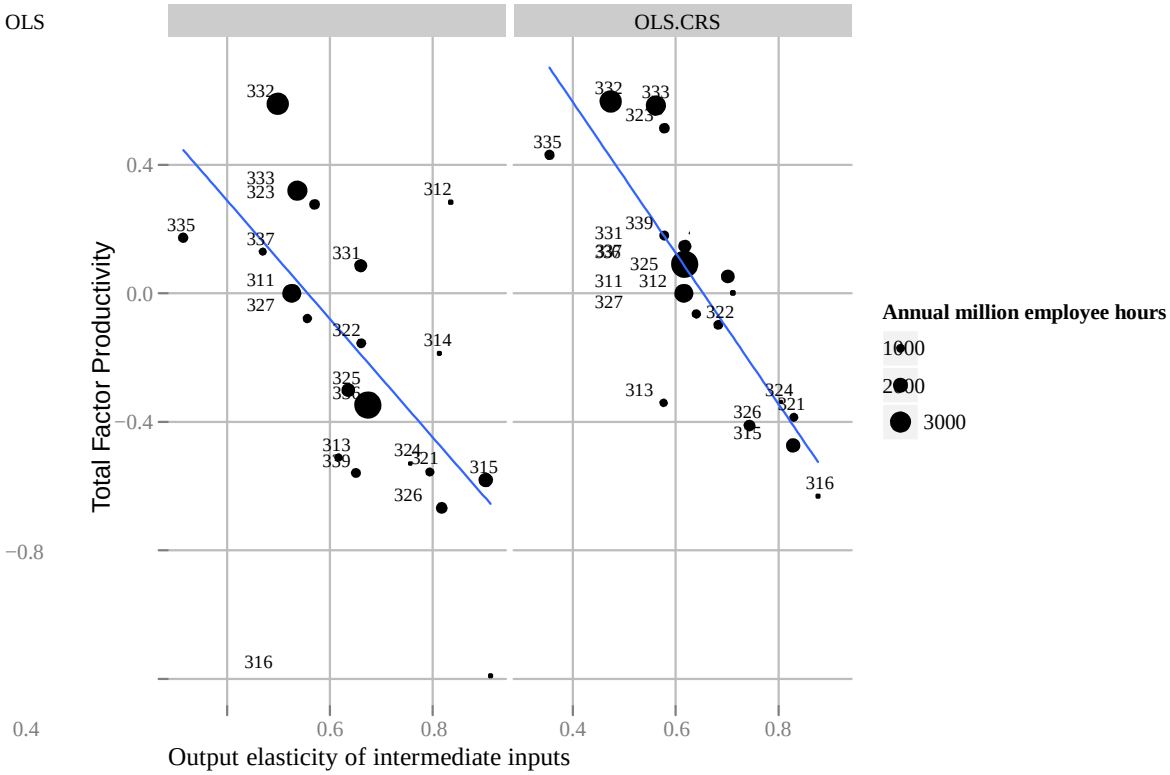

Figure 1. Intermediate input intensity (defined by the intermediate input output elasticity) and TFP in US manufacturing sectors estimated from an OLS production function. The line represents a simple employment-weighted OLS regression line for illustrative purposes only. The CRS suffix applies where constant returns to scale have been imposed.

intermediate input intensity. If the inverse relationship between TFP and intermediate input intensity also holds at the firm level as well as the sectorial level, this would suggest that results are not merely an artifact of sectorial composition (i.e. it just so happens that sectors with higher TFP use fewer intermediate inputs.) Figure 5 presents some indicative evidence at the firm level that this relationship between intermediate input intensity and total factor productivity is not purely a sectorial one. The data set used are a panel of 863 medium-sized manufacturing firms‡ from South Korea observed for three years from 1996 to 1998 from a survey conducted by the World Bank, see [37] for a full description of the data set (the ideal comparison, a panel of US firms from the sectors and years of the sectorial data was not accessible). Total factor productivity is calculated using a production function previously estimated using this data [9], and intermediate input intensity is calculated as intermediate inputs per unit of labour input.¶

‡ From the textile, garments, machinery, electronics and wood products sectors.

¶ Because a single production function was estimated for this dataset, β_M is the same for all firms, so an alternative measure of factor intensity was required. Using intermediate inputs per unit of output could not be used, because this could generate a spurious relationship: a hypothetical exogenous increase in total factor productivity would increase output per intermediate input even

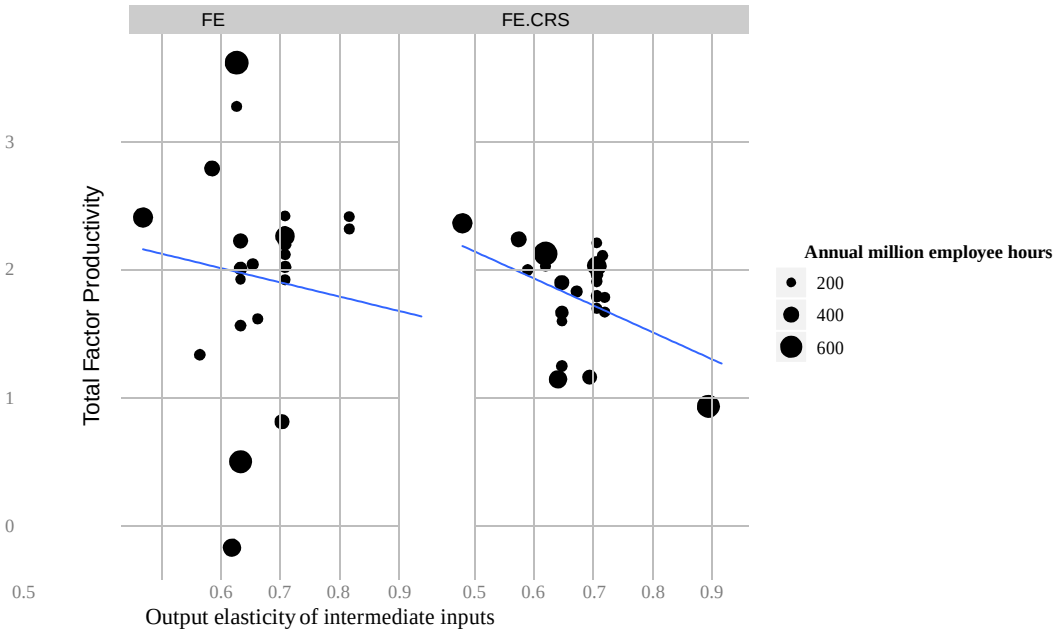

Figure 2. Intermediate input intensity (defined by the intermediate input output elasticity) and TFP in US manufacturing sectors estimated using the fixed effects estimator. The line represents a simple OLS regression line for illustrative purposes only. Note that all subsectors of each three-digit sector have the same intermediate input intensity coefficient by construction. The CRS suffix applies where constant returns to scale have been imposed.

Finally, we return to the value-added specification and the hypothesis derived in equation 2.7 that value-added estimates of total factor productivity are biased estimates of underlying total factor productivity, and that the size of this bias is increasing in intermediate input intensity. Value-added TFP is calculated by estimating equation 2.2 using OLS with constant returns to scale imposed (because income shares must necessarily sum to one in the value-added framework). The relationship between value-added TFP, gross-output TFP and intermediate input intensity can then be obtained from a suitable regression. Table 3 presents the results from an OLS estimation with value-added TFP and the dependent variable and gross output total factor productivity α and intermediate input intensity β_M as independent variables. As predicted by equation 2.7 the coefficient on α is equal to one, and the coefficient on β_M is positive. In short, firms with lower intermediate input intensity of production have higher TFP.

4. Policy implications

Some of the policy implications from our empirical results depend upon the conceptual basis for the relationship discovered between intermediate input intensity and TFP; that is, the precise nature of the unobserved factors driving TFP which

if there was no change in the manner in which intermediate inputs were used in the production process.

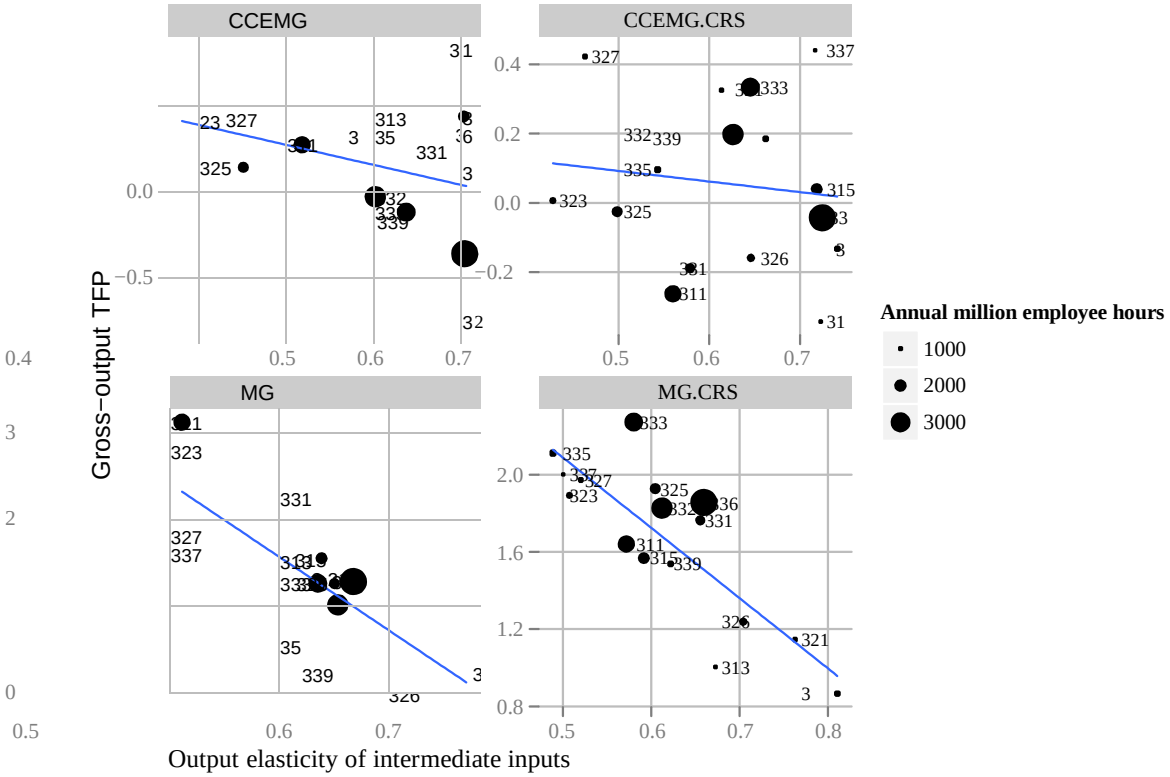

Figure 3. Intermediate input intensity (defined by the intermediate input output elasticity) and TFP in US manufacturing sectors estimated using the MG and CCEMG techniques. The line represents a simple OLS regression line for illustrative purposes only. Sectors with 10 or fewer groups have been excluded as these estimators perform poorly in such situations. The CRS suffix applies where constant returns to scale have been imposed.

are associated with intermediate input intensity. We find at least two possibilities plausible. First, because TFP captures all unobservables, if there are more positive spillovers from one factor of production than others, a higher intensity in that factor of production will be associated with higher TFP. For instance, it may be that there are positive externalities from human capital accumulation in the workforce [1]. This would explain why TFP is higher in industries that are more labour-intense. Other things equal (or indeed if capital use involves some positive externalities), it would follow that intermediate input-intensive industries, with lower intensity of capital and labour inputs, will be associated with lower TFP. Whether policies to reduce intermediate input use directly would themselves lead to increased TFP would depend upon the nature of the externalities.

Second, by analogy to Porter & van der Linde [57], it may be that firms that search for ways of lowering their intermediate input intensity also have higher TFP, either because the quest for reducing intermediate inputs creates other opportunities that are captured by the firms or, perhaps more likely, firms that are well-

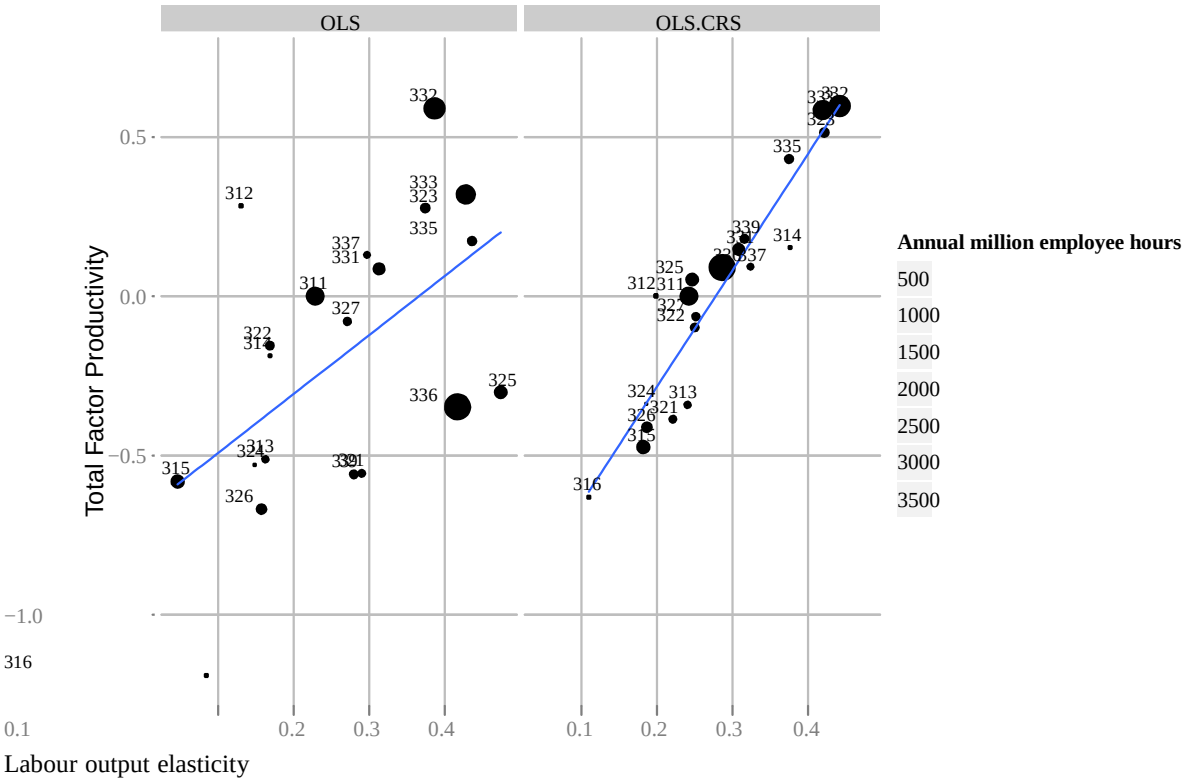

Figure 4. Labour intensity and TFP in US manufacturing sectors estimated from an OLS production function. The line represents a simple employment-weighted OLS regression line for illustrative purposes only.

managed are able to both reduce their intermediate input intensity and also deliver greater TFP as a result of superior management practices.

The broad observation that lower intermediate input intensity is associated with higher TFP potentially is not inconsistent with at least three specific policy recommendations (and there are potentially many others). First, irrespective of causality underpinning our results, it seems likely that productivity could be improved, and environmental and resource pressure reduced, by a reduction in the subsidies spent annually on materials and resource use. Such subsidies provide incentives for firms to increase intermediate input intensity which, as we have seen, is associated with lower TFP. Perhaps US $1 trillion is spent every year on directly subsidizing the consumption of resources [29]. This includes subsidies of approximately $400 billion on energy [41], around $200-300 billion of equivalent support on agriculture [54], very approximately US $200-300 billion on water [29], and approximately US $15-35 billion on fisheries [69]. To take one perverse example, subsidies worth 0.5% of EU GDP are spent annually on providing tax relief for company cars, which increases greenhouse gas emissions by between 4-8% [24].

While these direct subsidies are vast, they pale in comparison with the indirect subsidies in the form of natural assets that governments have failed to properly

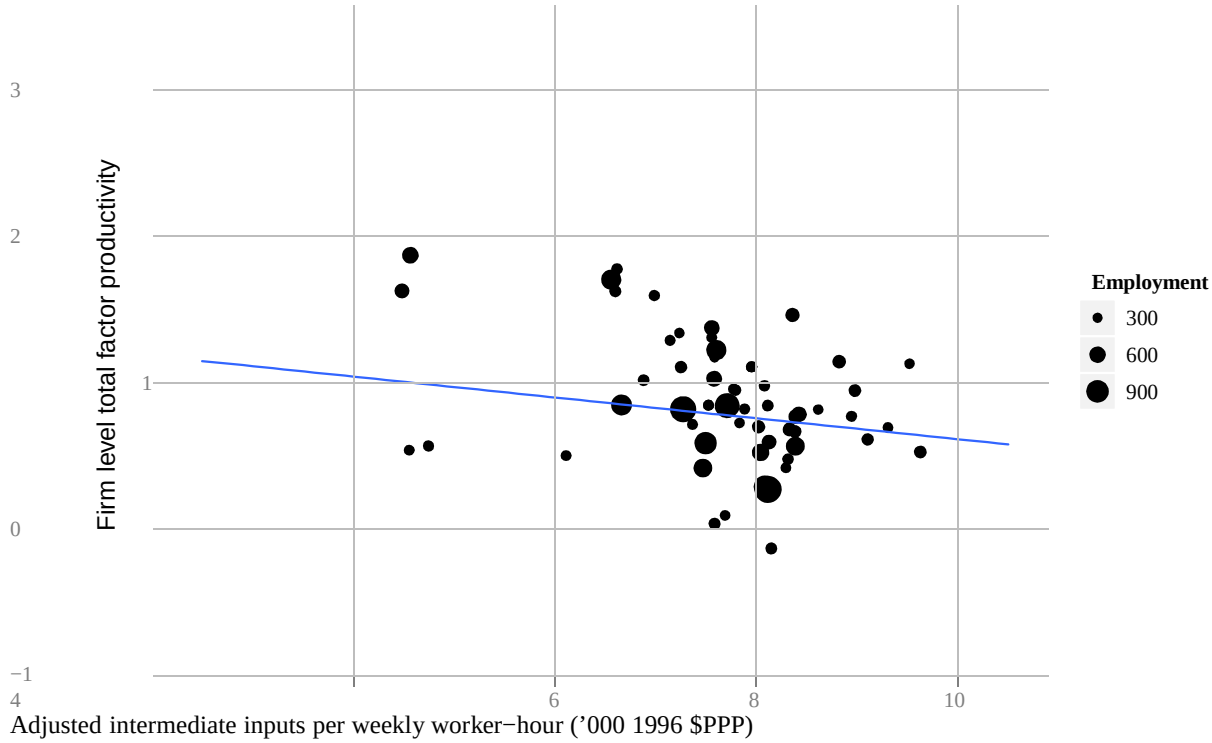

Figure 5. Intermediate input per worker and TFP in South Korean manufacturing firms based upon a production function estimated using system GMM. The line represents a simple employment-weighted OLS regression line for illustrative purposes only.

OLS (Intercept)		-0.41
		(0.88)
	Gross output TFP	1.00
(0.51) β_M		3.47*
		(1.41)
N		20
R^2		0.27
adj. R^2		0.18
Resid. sd		0.72

Table 3. *The dependent variable is value-added TFP. Standard errors in parenthesis and * indicates significance at* $p < 0.05$.

price. The indirect subsidy associated with lack of payments for biodiversity loss and other environmental costs is estimated at perhaps as much as $6.6 trillion [68].† Of this, US $1 trillion, very approximately, takes the form of subsidies for the use of

† This estimate should be viewed with high methodological scepticism and are vast underesti-

the atmosphere as a sink for greenhouse gas emissions [29]. By comparison, global GDP is around US $60 trillion at 2010 prices. Various countries, including Norway, Brazil and Australia have imposed explicit resource taxes, but taxes in one area do not undo the problems created by subsidies in another.

Second, productivity might be increased by other policies focused on reducing material intensity, beyond reducing perverse subsidies. One obvious example of this would be shifting the tax base away from labour, the factor input that correlates with higher TFP, and towards materials and resources, the factor correlated with lower TFP. This follows regardless of whether the results in this paper are driven by sectorial composition effects, or whether the relevant unobservables are directly related to material use within sectors. Taxing environmental externalities is obviously economically rational, as is taxing mineral rents [33] irrespective of other considerations. For instance, in contrast to the very substantial tax rates on labour, only a very small proportion of tax revenues are raised globally from taxation of resource use. For instance, even in OECD countries environmental taxes comprise only 6% of total tax revenues based on 2008 data; in the USA the proportion is around 3%, in the UK it is around 6%, while in the Netherlands it is above 10% [53].

Third, our results suggest that value-added measures of productivity, as commonly embodied in national accounting frameworks, may overstate the underlying gross output productivity of intermediate input-intensive sectors. As data from national accounts inform economic policy, it is possible that this systematic difference has led to policies which have sub-optimally increased the size of material-intensive sectors in the economy. National accounts should also endeavor to measure material use as well. If possible, material use should be further decomposed to separate energy and services from other natural resources and raw materials from purchased components.

5. Conclusion

This paper investigated the relationship between intermediate input intensity and total factor productivity. This was achieved through the estimation of gross output production functions for US industrial subsectors allowing for subsectoral heterogeneity in both of the key variables of interest: TFP and intermediate input intensity. The main limitations of the analysis, from the perspective of an interest in material use, due to stringent data requirements, were that results were based on data on 'intermediate inputs', of which materials form a major (but not exclusive) part, and were at the subsector level. A robustness check — using firm level-data — did not overturn the key conclusions.

There were three key results from our empirical analysis. First, there is a negative relationship between intermediate intensity and total factor productivity in the data examined. Second, there is a positive relationship between labour intensity and total factor productivity. Those sectors which are more intensive in their use of humans, rather than raw materials and other intermediate inputs, have higher levels of TFP, which means that a greater level of output is achieved from any given level

mates of infinity. Nevertheless, it can be taken as an indication that the scale of the 'subsidy' is extremely large.

of inputs. Firm-level evidence indicates that this relationship may not just be a result of sectorial composition. However, the determination of a causal impact within a sector of a reduction in intermediate input intensity increasing total factor productivity is left to future research, as is further narrowing to a definition of material inputs alone. Third, value-added measures of productivity, inherent in the national accounts of almost all countries, may systematically overstate the output-based productivity of material-intensive sectors. Changing national accounting frameworks to include material inputs, and improving the scope and quality of their measurement, should be a priority if natural resources are to be used efficiently and productivity maximised.

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